

VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum -590014, Karnataka.



LAB REPORT
on

Machine Learning (23CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING



B.M.S. COLLEGE OF ENGINEERING

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Department of Computer Science and Engineering



CERTIFICATE

This is to certify that the Lab work entitled “Machine Learning (23CS6PCMAL)” carried out by Araga Laxman Anirudhadithya(1BM22CS050), who is Bonafide student of **B.M.S. College of Engineering**. It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements in respect of a Machine Learning (23CS6PCMAL) work prescribed for the said degree.

Lab Faculty Incharge Name: Ms. Saritha A N Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE
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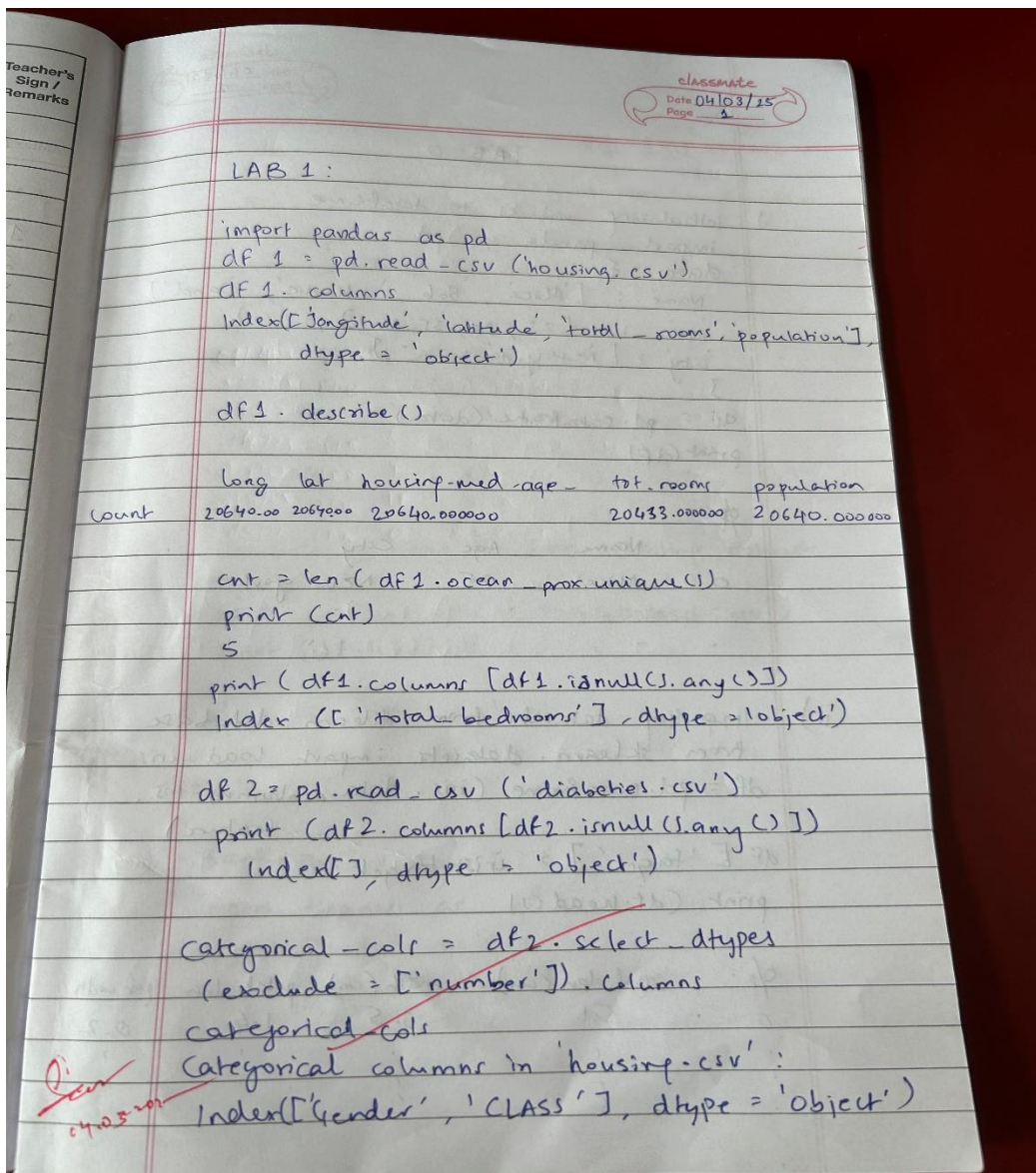
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Program 1

Write a python program to import and export data using Panda's library functions

Screenshot



Code:

```
import pandas as pd

try:
    df = pd.read_csv('input.csv')
    print("Data imported successfully!\n")
    print(df)
except FileNotFoundError:
    print("The file 'input.csv' was not found.")

df["Processed"] = True

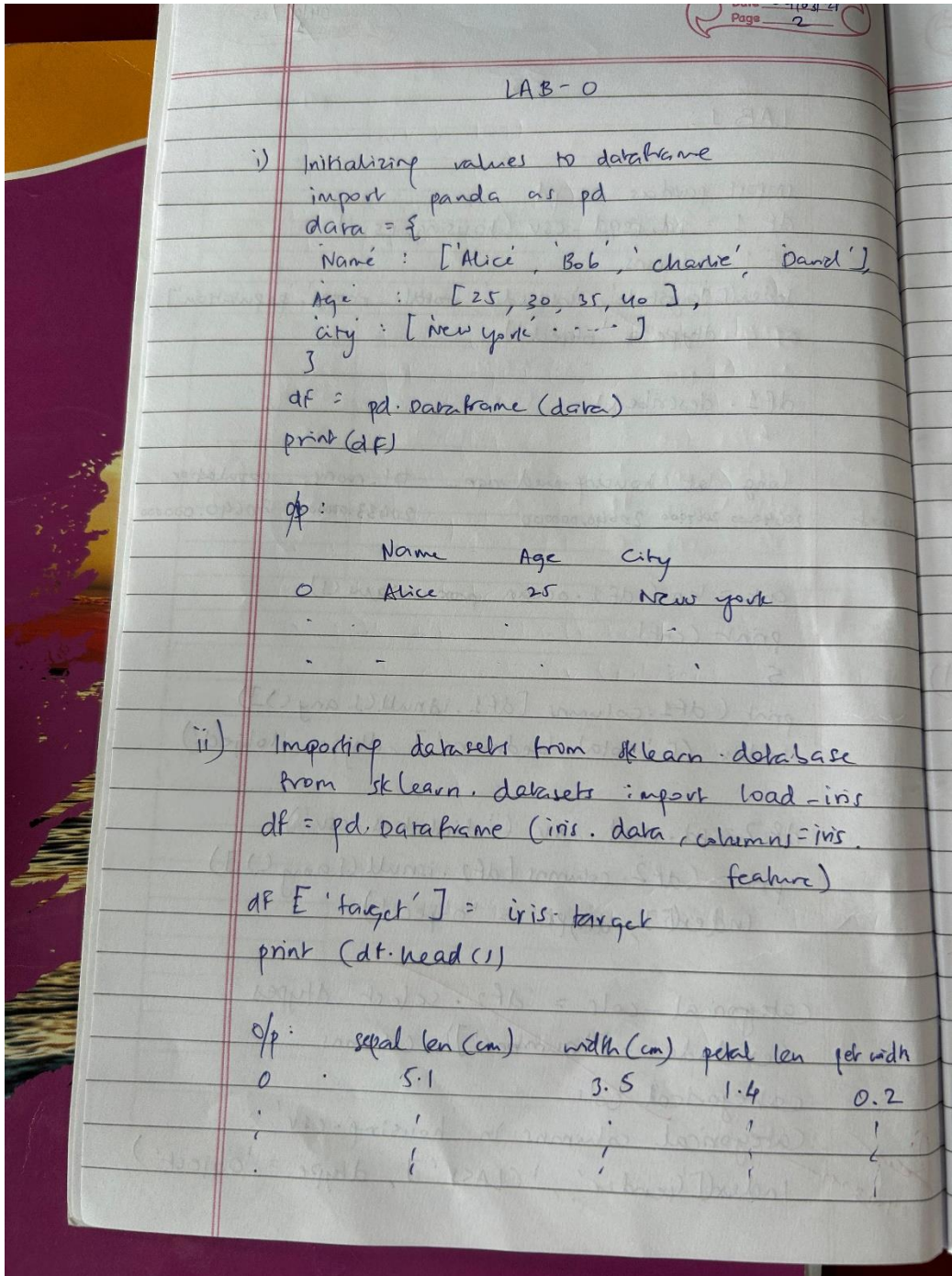
df.to_csv('output.csv', index=False)

print("\nData exported successfully to 'output.csv'.")
```

Program 2

Demonstrate various data pre-processing techniques for a given dataset

Screenshots:



Code

```
import pandas as pd
```

```
import numpy as np
```

```
from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler
```

```
data = {
```

```
    'Name': ['Alice', 'Bob', 'Charlie', 'David', 'Eve', None],
```

```
    'Age': [25, 30, np.nan, 35, 29, 40],
```

```

    'Department': ['HR', 'IT', 'Finance', 'IT', 'HR', 'Finance'],
    'Salary': [50000, 60000, 58000, 62000, np.nan, 52000]
}

df = pd.DataFrame(data)

print("Original DataFrame:\n", df)

df['Age'].fillna(df['Age'].mean(), inplace=True)
df['Salary'].fillna(df['Salary'].median(), inplace=True)
df['Name'].fillna('Unknown', inplace=True)

le = LabelEncoder()
df['Department_Encoded'] = le.fit_transform(df['Department'])

df.drop_duplicates(inplace=True)

df.rename(columns={'Salary': 'Monthly_Salary'}, inplace=True)

df['Age'] = df['Age'].astype(int)

scaler = MinMaxScaler()
df['Salary_Normalized'] = scaler.fit_transform(df[['Monthly_Salary']])

standard_scaler = StandardScaler()

```



```
df['Age_Standardized'] = standard_scaler.fit_transform(df[['Age']])
```

```
print("\nPreprocessed DataFrame:\n", df)
```

Program 3

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

Screenshots

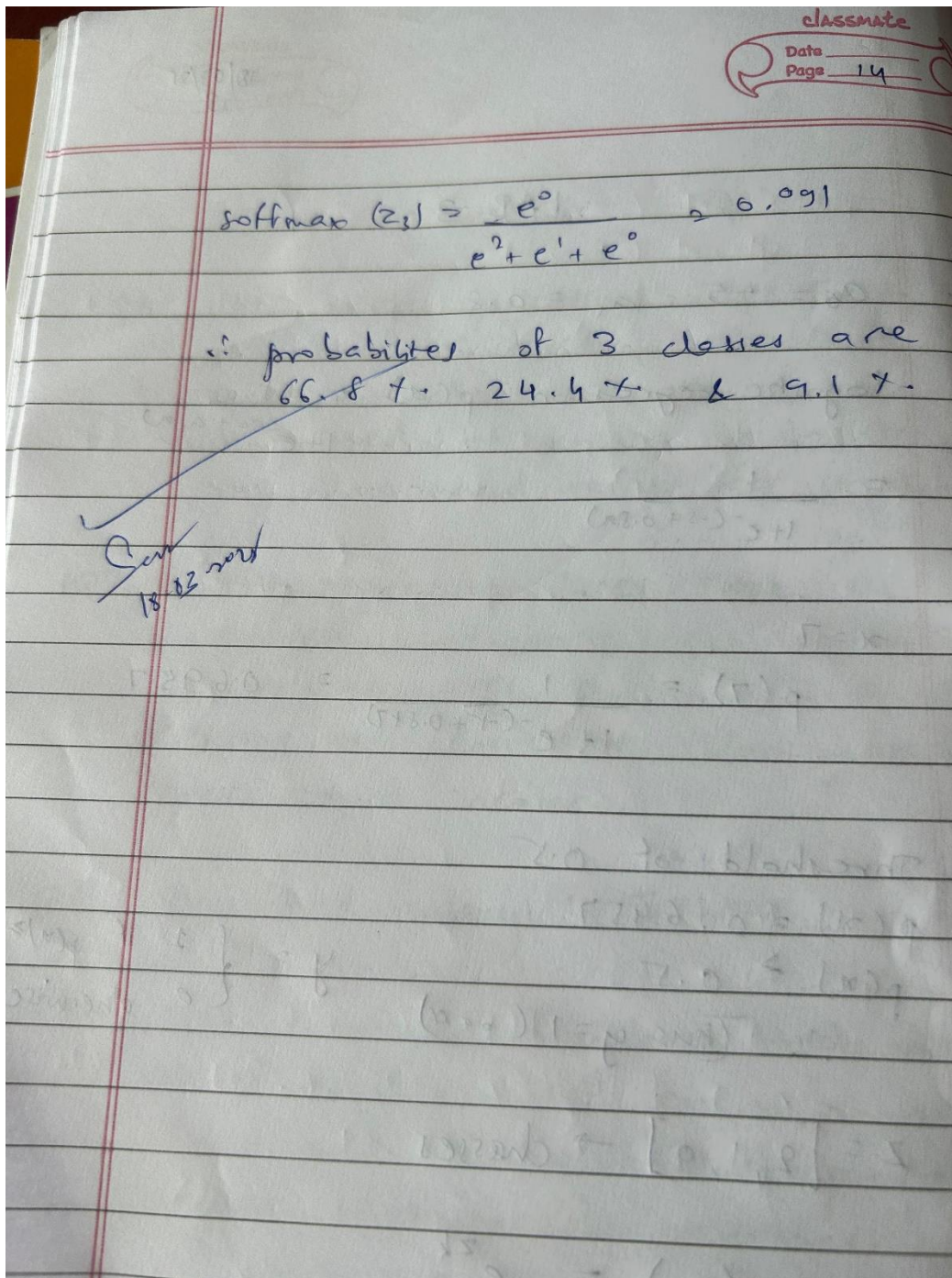
classmate
Date 11/03/25
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LAB-4

Find linear regression of the data of work and product.

week	sales
x	y
1	2
2	4
3	5
4	9

$$X^T = [1 \ 2 \ 3 \ 4]$$
$$Y^T = [2 \ 4 \ 5 \ 9]$$
$$X^T X = \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 \end{pmatrix} \times \begin{pmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{pmatrix}$$
$$= \begin{pmatrix} 4 & 10 \\ 10 & 30 \end{pmatrix}$$
$$(X^T X)^{-1} = \begin{pmatrix} 4 & 10 \\ 10 & 30 \end{pmatrix}^{-1} = \begin{pmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{pmatrix}$$
$$\left(\begin{pmatrix} 1.5 & -0.5 \\ -0.5 & 0.2 \end{pmatrix} \begin{pmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 \end{pmatrix} \right) \begin{pmatrix} 1 \\ 2 \\ 4 \\ 9 \end{pmatrix}$$



Code

Linear Regression

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_boston
from sklearn.linear_model import LinearRegression
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.metrics import mean_squared_error, r2_score

# Load dataset
boston = load_boston()
df = pd.DataFrame(boston.data, columns=boston.feature_names)
df['PRICE'] = boston.target

# Use only one feature for simple linear regression (e.g., RM = average number of rooms)
X = df[['RM']]
y = df['PRICE']

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

# Train model
lr = LinearRegression()
lr.fit(X_train, y_train)
```

```

# Predict
y_pred = lr.predict(X_test)

# Output
print("Linear Regression Results")
print("Coefficients:", lr.coef_)
print("Intercept:", lr.intercept_)
print("MSE:", mean_squared_error(y_test, y_pred))
print("R2 Score:", r2_score(y_test, y_pred))

# Plot
plt.scatter(X_test, y_test, color='blue')
plt.plot(X_test, y_pred, color='red')
plt.xlabel('Average Number of Rooms (RM)')
plt.ylabel('House Price')
plt.title('Simple Linear Regression')
plt.show()

# Multiple Linear Regression

# Use all features
X = df.drop('PRICE', axis=1)
y = df['PRICE']

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

# Train model
mlr = LinearRegression()
mlr.fit(X_train, y_train)

# Predict
y_pred = mlr.predict(X_test)

# Output
print("\nMultiple Linear Regression Results")
print("Coefficients:", mlr.coef_)
print("Intercept:", mlr.intercept_)
print("MSE:", mean_squared_error(y_test, y_pred))
print("R2 Score:", r2_score(y_test, y_pred))

```

Program 4

Build Logistic Regression Model for a given dataset

LAB -3

1. $a_0 = -5$ $a_1 = 0.8$

logistic regression $p(x) = \frac{1}{1 + e^{-(a_0 + a_1 x)}}$
 $= \frac{1}{1 + e^{-(-5 + 0.8x)}}$

2. $x = 7$

$p(7) = \frac{1}{1 + e^{-(-5 + 0.8 \times 7)}} = 0.6957$

3. Threshold at 0.5

$p(x) = 0.6457$

$p(x) \geq 0.5$

\therefore Thus $y = 1$ ($p < 0.5$)

$y = \begin{cases} 1 & \text{if } p(x) \geq 0.5 \\ 0 & \text{otherwise} \end{cases}$

4. $Z = [2, 1, 0] \rightarrow$ classes

$\rightarrow \text{softmax}(Z_0) = \frac{e^{Z_0}}{\sum_{j=1}^3 e^{Z_j}}$

$\text{softmax}(Z_0) = \frac{e^2}{e^2 + e^1 + e^0} = 0.665$

$\text{softmax}(Z_2) = \frac{e^1}{e^2 + e^1 + e^0} = 0.244$

Screenshot's

Code

```
import pandas as pd

from sklearn.datasets import load_iris

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

iris = load_iris()

df = pd.DataFrame(iris.data, columns=iris.feature_names)

df['species'] = iris.target
```



```

df_binary = df[df['species'] != 2] # Remove class 2 (Virginica)

X = df_binary.iloc[:, :-1] # Features
y = df_binary['species']    # Target (0 or 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = LogisticRegression()
model.fit(X_train, y_train)

# Step 5: Predict and evaluate
y_pred = model.predict(X_test)

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nAccuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

```

Program 5

Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample

Screenshots

LAB-5

Decision tree

Q. Instance a_2 a_3 Classification

1	Hot	high	No
2	Hot	high	No
3	Cool	high	No
7	Hot	high	No
8	Hot	normal	Yes

→ Entropy (S) = $-\frac{4}{5} \log(\frac{4}{5}) - \frac{1}{5} \log(\frac{1}{5})$

for A_2

$S_{\text{Hot}} [1+, 3-] = -\frac{1}{4} \log(\frac{1}{4}) - \frac{3}{4} \log(\frac{3}{4})$
 $= 0.8119$

Gain = 0.01284

for A_3

$S_{\text{High}} = [0+, 0-] = 0$
 $S_{\text{Normal}} = [1+, 0+] = 0$
 $\text{Gain}(S, A_3) = 0.7219$

```

graph TD
    A((a3)) -- High --> B((a2))
    A -- Normal --> C((a2))
    B -- Hot --> D[1, 2, 6]
    B -- Cool --> E[ ]
    C -- Hot --> F[ ]
    C -- Cool --> G[ ]
    style E fill:none,stroke:none
    style F fill:none,stroke:none
    style G fill:none,stroke:none
    
```

(1, 2, 7) 6 8 -

$$\begin{aligned} \alpha_1 \hat{s}_1 \hat{s}_1 + \alpha_2 \hat{s}_2 \hat{s}_1 + \alpha_3 \hat{s}_3 \hat{s}_1 &= +1 \\ \alpha_1 \hat{s}_1 \hat{s}_2 + \alpha_2 \hat{s}_2 \hat{s}_2 + \alpha_3 \hat{s}_3 \hat{s}_2 &= +1 \\ \alpha_1 \hat{s}_1 \hat{s}_3 + \alpha_2 \hat{s}_2 \hat{s}_3 + \alpha_3 \hat{s}_3 \hat{s}_3 &= -1 \end{aligned}$$

after sub.

$$\alpha_1 = 13/4$$

$$\alpha_2 = 13/4$$

$$\alpha_3 = -7/2$$

$$L = \alpha_1 \hat{s}_1 + \alpha_2 \hat{s}_2 + \alpha_3 \hat{s}_3$$

$$= - \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad b = -3$$

$$b + 3 = 0$$

intercept on x axis = 3

~~$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$~~ → line parallel to y axis.

Code

```
import pandas as pd
```

```

from sklearn.preprocessing import LabelEncoder

from sklearn.tree import DecisionTreeClassifier

from sklearn import tree

data= {

    'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Rain', 'Overcast',
               'Sunny', 'Sunny', 'Rain', 'Sunny', 'Overcast', 'Overcast', 'Rain'],
    'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool',
                   'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'],
    'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal', 'Normal',
                'High', 'Normal', 'Normal', 'Normal', 'High', 'Normal', 'High'],
    'Wind': ['Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong',
            'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Strong'],
    'PlayTennis': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes',
                  'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
}

```

```
df=pd.DataFrame(data)
```

```
le = LabelEncoder()
```

```
for column in df.columns:
```

```
    df[column] = le.fit_transform(df[column])
```

```
#Step 3: Separate features and label
```

```
X = df.drop('PlayTennis', axis=1)
```

```
y = df['PlayTennis']
```

```
clf= DecisionTreeClassifier(criterion='entropy') #ID3 uses 'entropy'
```

```

clf = clf.fit(X, y)

print("\nDecision Tree Rules:")

tree_text = tree.export_text(clf, feature_names=X.columns.tolist())

print(tree_text)

# Example: Outlook=Rain, Temperature=Mild, Humidity=High, Wind=Weak

# Encode input sample with same label encoding order used earlier

sample = pd.DataFrame({

    'Outlook': [le.transform(['Rain'])[0]],

    'Temperature': [le.transform(['Mild'])[0]],

    'Humidity': [le.transform(['High'])[0]],

    'Wind': [le.transform(['Weak'])[0]]

})

# Predict

prediction = clf.predict(sample)

result = 'Yes' if prediction[0] == 1 else 'No'

print(f"\nPrediction for new sample (Rain, Mild, High, Weak): {result}")

```

Program 6 Build KNN Classification model for a given dataset

LAB - 6

KNN :

q.

Person	Age	Sal.	Target	distance
A	18	50	N	52.8
B	23	55	N	46.57
C	29	70	N	31.95
D	41	60	Y	46.44
E	43	70	Y	31.04
F	38	60	Y	60.07
X	35	100	Y	?

$x = (35, 100)$

$k = 3$

Dist	Rank	Target
31.04	1	Y
31.95	2	N
46.44	3	Y

$x(35, 100)$ target will be Y.

Code

```
import pandas as pd
```

```
from sklearn.datasets import load_iris
```

```
from sklearn.model_selection import train_test_split
```



```
from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix


# Step 1: Load the Iris dataset

iris = load_iris()

X = pd.DataFrame(iris.data, columns=iris.feature_names)
```

```

y = pd.Series(iris.target)

# Step 2: Split the data (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 3: Build KNN model (k = 3)
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)

# Step 4: Predict and evaluate
y_pred = knn.predict(X_test)

# Results
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("Accuracy Score:", accuracy_score(y_test, y_pred))

```

Program 7

Build Support vector machine model for a given dataset

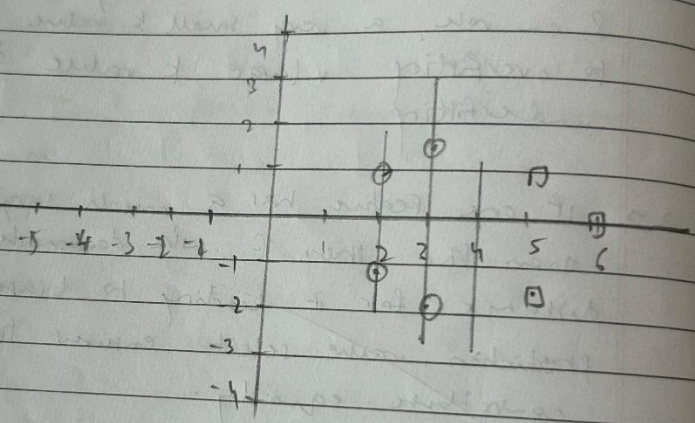
Screenshots

LAB 7:

Draw an optimal hyperplane using linear sum to classify points.

$\{ (1,1), (2,1), (1,-1), (2,-1) \} \rightarrow$ red class

$\{ (4,0), (5,1), (5,-1), (6,0) \} \rightarrow$ blue class



$$S_1 = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix} \quad S_2 = \begin{bmatrix} 2 \\ -1 \\ -1 \end{bmatrix} \quad S_3 = \begin{bmatrix} 4 \\ 0 \\ 0 \end{bmatrix}$$

$$\bar{S}_1 = \begin{bmatrix} 2 \\ 1 \\ 1 \end{bmatrix} \quad \bar{S}_2 = \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix} \quad \bar{S}_3 = \begin{bmatrix} 4 \\ 0 \\ 1 \end{bmatrix}$$

Code

```
import pandas as pd

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.svm import SVC

from sklearn.metrics import confusion_matrix, classification_report, accuracy_score


# Step 1: Load the Iris dataset

iris = load_iris()

X = pd.DataFrame(iris.data, columns=iris.feature_names)

y = pd.Series(iris.target)


# Step 2: Split the data into train and test sets (80% train, 20% test)
```

```
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.2, random_state=42)

#Step 3: Build and train the SVM model(linear kernel)

svm_model = SVC(kernel='linear')

svm_model.fit(X_train, y_train)

# Step 4: Predict and evaluate

y_pred=svm_model.predict(X_test)

# Output results

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

print("\nClassification Report:\n", classification_report(y_test, y_pred))

print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

Program 8

Implement Random Forest ensemble method on a given dataset

Screenshots

LAB 5:

Decision tree

1. Single tree
2. Risk accurate
2. Fast to train
4. Single prediction

Random forest

1. Multiple
2. More accurate
3. Slow to train
4. Majority vote

Parameters of random forest class.

- n: estimate no. of trees in forest
- max depth & min depth of tree.

Algo:

1. Training dataset:

2. for n times:

- Randomly select samples w replacement
- grow a decision tree
- split nodes using best features.

3. Aggregate pred:

- Class = Maj. vote
- Regression = Avg.

4. O/p prediction

code:

```
import pandas as pd
from sklearn import selection
import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

```
x_train, y_train, x_test, y_test = train_test_split(
    x, y, test_size=0.2, random_state=42)
```

```
rf = RandomForestClassifier(n_estimators=10, random_state=42)
```

```
rf.fit(x_train, y_train)
```

```
y_pred = rf.predict(x_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
```

```
print(accuracy)
```

```
estimator = [10, 50, 100, 200, 500]
```

```
scores = []
```

```
for estimator in estimator:
```

```
    rf = RandomForestClassifier(n_estimators=estimator,
                               random_state=42)
```

```
    rf.fit(x_train, y_train)
```

```
    y_pred = rf.predict(x_test)
```

```
    score = accuracy_score(y_test, y_pred)
```

```
    scores.append(score)
```

```
print(scores)
```

Code

```
import pandas as pd

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score


# Step 1: Load Iris dataset

iris = load_iris()

X = pd.DataFrame(iris.data, columns=iris.feature_names)

y = pd.Series(iris.target)
```



```
# Step 2: Split into train and test sets (80% train, 20% test)

X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.2, random_state=42)


# Step 3: Train Random Forest model

rf=RandomForestClassifier(n_estimators=100, random_state=42) # 100 trees

rf.fit(X_train, y_train)


# Step 4: Predict and evaluate

y_pred = rf.predict(X_test)


print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

print("\nClassification Report:\n", classification_report(y_test, y_pred))

print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

Program 9

Implement Boosting ensemble method on a given dataset

Screenshots

LAB-9 :

Boosting :

Combines multiple weak learners to create a ~~strong~~ strong learner. It works by training modules sequentially where each next one uses the previous one's output.

Parameters :

Estimator The base model

n -estimator no. of weak learners.

Learning-rate Shrinks contribution of each learner
algo 'SAMME' or 'SAMME-PT'

random-state for reproducibility

Algorithm :

1. Start w eq. wts for all training for each sample
2. train a weak model
3. calc. error & update sample wts.
4. Add weak model to ensemble w c wt based on its accuracy.
5. Repeat for n -estimators
6. final prediction.

Code

```
import pandas as pd

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.ensemble import AdaBoostClassifier

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

from sklearn.tree import DecisionTreeClassifier


#Step 1: Load the Iris dataset

iris = load_iris()
```

```

X=pd.DataFrame(iris.data, columns=iris.feature_names)

y = pd.Series(iris.target)


# Step 2: Split into train and test sets (80% train, 20% test)

X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.2, random_state=42)


# Step 3: Build AdaBoost modelwith DecisionTreeClassifier as base estimator

base_estimator = DecisionTreeClassifier(max_depth=1)

model= AdaBoostClassifier(base_estimator=base_estimator, n_estimators=50, learning_rate=1.0,
random_state=42)

model.fit(X_train, y_train)


# Step 5: Predict and evaluate

y_pred=model.predict(X_test)

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

print("\nClassification Report:\n", classification_report(y_test, y_pred))

print("Accuracy Score:", accuracy_score(y_test, y_pred))

```

Program 10

Build k-Means algorithm to cluster a set of data stored in a .CSV file

Screenshots

Code

```
import pandas as pd

from sklearn.cluster import KMeans

import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler


# Step 1: Load dataset from CSV

df = pd.read_csv('your_dataset.csv') # Replace with your file path


# Optional: View first few rows

print("Data Preview:\n", df.head())
```

```

# Step 2: Select relevant numeric columns for clustering

# You can specify specific columns like: df[['column1', 'column2']]

X = df.select_dtypes(include='number')


# Step 3: Scale the data (important for K-Means)

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)


# Step 4: Apply K-Means clustering (e.g., 3 clusters)

kmeans = KMeans(n_clusters=3, random_state=42)

df['Cluster'] = kmeans.fit_predict(X_scaled)


# Step 5: Print cluster centers

print("Cluster Centers:\n", kmeans.cluster_centers_)


# Optional Step 6: Visualize (works well for 2D or PCA-reduced data)

if X.shape[1] >= 2:

    plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=df['Cluster'], cmap='viridis')

    plt.title("K-Means Clustering")

    plt.xlabel("Feature 1")

    plt.ylabel("Feature 2")

    plt.show(

```

code:

```
import pandas as pd
from sklearn.feature_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

```
x_train, y_train, x_test, y_test = train_test_split(
    x, y, test_size=0.2, random_state=42)
```

```
rf_default = RandomForestClassifier(n_estimators=10,
    random_state=42)
```

```
rf_default.fit(x_train, y_train)
```

```
y_pred_default = rf_default.predict(x_test)
```

```
accuracy_default = accuracy_score(y_test, y_pred)
```

```
print(accuracy_default)
```

```
estimator = [10, 50, 100, 200, 500]
```

```
scores = []
```

```
for estimator in estimator:
```

```
    rf = RandomForestClassifier(n_estimators=estimator,
    random_state=42)
```

```
    rf.fit(x_train, y_train)
```

```
    y_pred = rf.predict(x_test)
```

```
    score = accuracy_score(y_test, y_pred)
```

```
    scores.append(score)
```

```
print(scores)
```


Program 11

Implement Dimensionality reduction using Principal Component Analysis (PCA) method

Screenshots

Lab 10 : PCA

1. Calculate Mean
2. Calculate covariance matrix
3. Eigen val of covariance matrix
4. Computation of eigen vectors with eigen vectors
5. Computation of first principle component
6. Geometric mean of 1st principle component

x_1	x_2	x_3	x_4	x_5
4	8	13	13	7
11	4	5	5	14

calculate mean

$$\bar{x}_1 = 1/4 (4 + 11 + 13 + 13 + 14)$$

$$\bar{x}_2 = 1/4 (8 + 4 + 5 + 5 + 14) = 8.5$$

$$\begin{aligned} \text{Cov}(x_1, x_2) &= 1/N \sum_{i=1}^N (x_{1i} - \bar{x}_1)(x_{2i} - \bar{x}_2) \\ &= 1/5 [(4-8)(8-8.5) + (11-8)(4-8.5) + (13-8)(5-8.5) + (13-8)(5-8.5) + (14-8)(14-8.5)] \\ &= -11 \end{aligned}$$

$$S = \begin{bmatrix} \text{Cov}(x_1, x_1) & \text{Cov}(x_1, x_2) \\ \text{Cov}(x_2, x_1) & \text{Cov}(x_2, x_2) \end{bmatrix}$$

$$S = \begin{bmatrix} 14 & -11 \\ -11 & 23 \end{bmatrix}$$

ii)

$$\text{Eigen value} = \begin{bmatrix} 14 - \lambda & -11 \\ -11 & 23 - \lambda \end{bmatrix}$$

Code

```
import pandas as pd

from sklearn.datasets import load_iris

from sklearn.preprocessing import StandardScaler
```

```
from sklearn.decomposition import PCA
```

```
import matplotlib.pyplot as plt
```

```
# Step 1: Load the Iris dataset
```

```
iris = load_iris()
```

```
X = iris.data
```

```

y = iris.target

feature_names = iris.feature_names


# Step 2: Standardize the data

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)


# Step 3: Apply PCA (reduce to 2 components for visualization)

pca = PCA(n_components=2)

X_pca = pca.fit_transform(X_scaled)


# Step 4: Plot the 2D PCA result

plt.figure(figsize=(8, 6))

scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis', edgecolor='k', s=60)

plt.xlabel("Principal Component 1")

plt.ylabel("Principal Component 2")

plt.title("PCA - Iris Dataset")

plt.legend(handles=scatter.legend_elements()[0], labels=iris.target_names)

plt.grid(True)

plt.show()


# Explained variance

print("Explained variance ratio:", pca.explained_variance_ratio_)

```